Assimilation of Satellite Precipitation and Soil Moisture Data into the WRF-Noah Model

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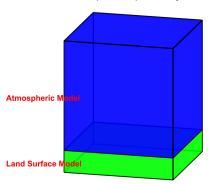
Outline

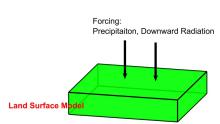
- Research Background and Motivations
- Joint Data Assimilation System and Experiment Setup
- Evaluation of Precipitation Analyses and Forecasts
- Evaluation of Soil Moisture
- Summary and Future Work

 Atmospheric and land surface data assimilation have been developed separately for a long time

Research Background and Motivations

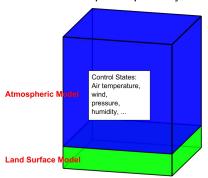
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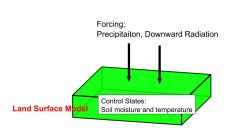


Research Background and Motivations

 Atmospheric and land surface data assimilation have been developed separately for a long time



- Atmospheric Data Assimilation System:
 - Using mostly variational data assimilation
 - Fixing land surface states during the analysis procedure



- Land Surface Data Assimilation System:
 - Using mostly ensemble-based filtering
 - Updating only land surface states in the analysis procedure

Research Background and Motivations

Background

- Atmospheric and land surface data assimilation have been developed separately for a long time
- The available data assimilation systems do not allow us to study the relative impact of remotely-sensed precipitation and soil moisture (two of the most important variables in hydrologic cycles) on short-term precipitation and soil moisture predictions.

Background

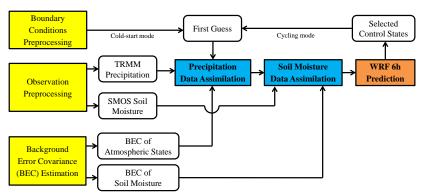
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- The available data assimilation systems do not allow us to study the relative impact of remotely-sensed precipitation and soil moisture (two of the most important variables in hydrologic cycles) on short-term precipitation and soil moisture predictions.
 - Precipitation: TRMM, GPM
 - Soil Moisture: SMOS, AMSR-E, SMAP

Joint Data Assimilation System

- The coupled WRF-Noah model
- Similar data assimilation approaches for both atmospheric and soil moisture states:
 - Variational data assimilation scheme
 - National Meteorological Center (NMC) method for estimating the background error covariance

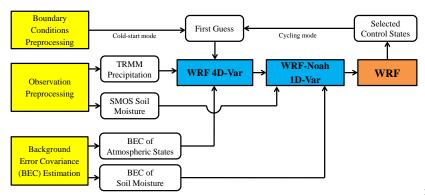
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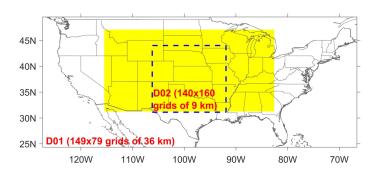


Joint Data Assimilation System

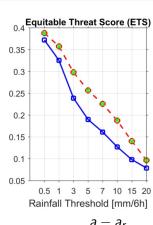
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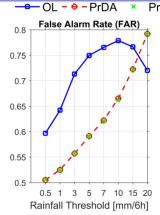
Experiment Setup



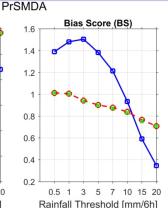
- Experiment duration: July 1-29, 2013
- Experiments:
 - OL: no data assimilation
 - PrDA: assimilation of six-hour TMPA 3B42 precipitation data
 - PrSMDA: assimilation of six-hour TMPA 3B42 precipitation and orbital SMOS soil moisture data



$$ETS = \frac{a - a_r}{a + b + c - a_r}$$



 $FAR = \frac{b}{a+b}$

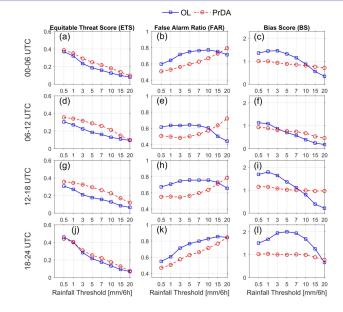


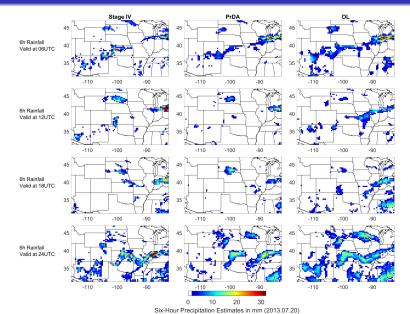
 $BS = \frac{a+b}{a+c}$

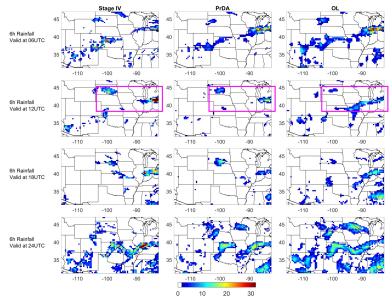
$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} hits & falsealarms \\ misses & noforecasts \end{bmatrix}$$

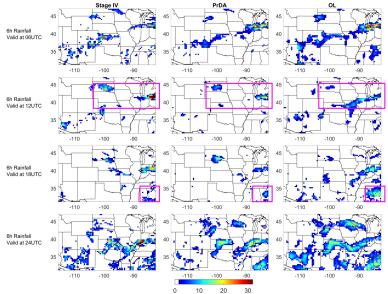
$$a_r = \frac{(a+b)(a+c)}{n}$$

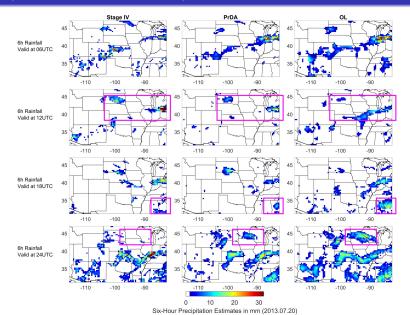
Score of the Precipitation Analyses (Different Times)



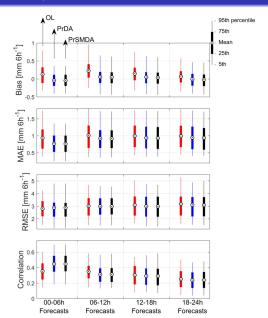








Statistics of Precipitation Forecasts



32 -106

-104

SCAN 2072 **CRN NE Harrison 20SSE** CRN NE Whitman 5ENE SCAN 2068 CRN NE Lincoln 8ENE 42 •CRN IA Des Moines 17I **SCAN 2017** SCAN 2001 **CRN NE Lincoln 11SW SCAN 2047** 40 SCAN 2093 SCAN 2094 CRN MO Chillicothe 22 SCAN 2147 **CRN KS Oakley 19SSW** SCAN 2061 CRN MO Joplin 24N 38 SCAN 2092 SCAN 2194 CRN OK Goodwell 2SE CRN OK Stillwater 5WNW 36 SCAN 2006 CRN TX Muleshoe 19S 34

-98

-96

-94

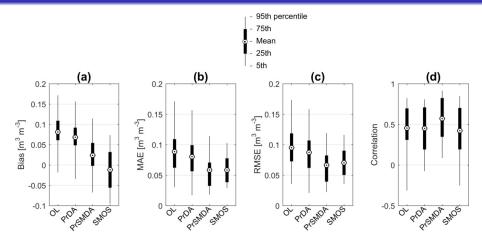
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- -100 SCAN: Soil Climate Analysis Network
- CRN: Climate Reference Network

SCAN 2105 SCAN 2107 **SCAN 2108**

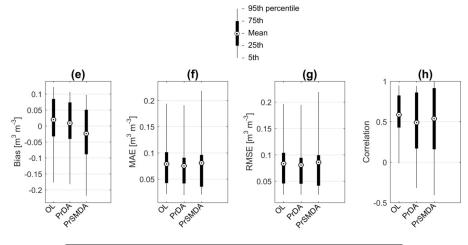
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Statistics of Hourly Top 10-cm Soil Moisture Comparison



Experiment\Improvement in	Bias	MAE	RMSE	Corr
PrDA	16%	9%	8%	-1%
PrSMDA	71%	34%	30%	21%

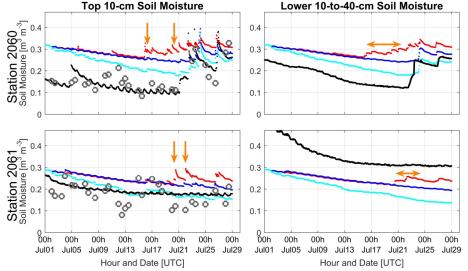
Statistics of Hourly 10-to-40-cm Soil Moisture Comparison



Experiment\Improvement in	Bias	MAE	RMSE	Corr
PrDA	56%	5%	3%	-23%
PrSMDA	-21%	-2%	-6%	-12%

Selected Time Series

OL
PrDA
PrSMDA
SCAN Obs.
SMOS Obs.



Summary and Future Directions

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- Assimilation of TMPA 3B42 precipitation improves precipitation analyses significantly but its benefit drops quickly beyond the assimilation window.
- Assimilation of SMOS soil moisture has only marginal effect on precipitation analyses/forecasts.
- Both precipitation and soil moisture data assimilation can reduce surface soil moisture simulations, while has small to negative impact on lower layer soil moisture simulations.

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Future Directions

- Bias characterization of satellite and model soil moisture data
- Assimilation of IMERG precipitation and SMAP soil moisture
- Assimilation of radiance observations from GPM constellation

Thank you!

Acknowledgments

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